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Development and application of a model for the automatic evaluation and classification of onions (*Allium cepa* L.) using a Deep Neural Network (DNN)

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ABSTRACT

Evaluating onions for size, shape, damage, colour and discolouration is the first and most important step in classifying them for raw material quality, processing and the horticultural and agri-food sectors. Current methods of geometric evaluation and grading of onions involve mechanical and extremely invasive sorting, which causes additional damage, reduces the quality of the raw material and is also labour and time-consuming. As a result, non-invasive evaluation and classification methods that are both fast and accurate are being sought. One such method is digital image analysis, which, when combined with instrumentation and deep neural networks, can fully automate the process. The main aim of this study was the development of a model for the automatic evaluation and classification of onions using a deep convolutional neural network (CNN) model. A fixed-architecture network was built, for which a computational algorithm was developed in Python 3.9 and published at https://github.com/piotrrybacki/onion-CNN.git (accessed on 4 October 2024). The Hyduro F1 onion variety, a hybrid all-purpose variety of the Rijnsburger type, was used to build, teach and test the model. The developed algorithm classified the onion images qualitatively with an accuracy of 91.85%. This classification was based on the geometric parameters of the onion, i.e. diameter, height, transversal and longitudinal circumference, and the estimated area of damage or discolouration of the skin. The root mean square error (MSE) in RGB space varied between 87.99 and 91.24, and the maximum image classification time was 28.98 ms/image. The developed algorithm has a very high utility, as it automates the classification process, reducing its time and labour intensity.

Keywords: automatic evaluation, convolutional neural network, digital image analysis, onion quality, machine learning

INTRODUCTION

Onions (*Allium cepa* L.) are one of the world's staple vegetables, belonging to the genus Allium, which includes more than 700 plant species and are native to western Asia, where they have been known for about 7,000 years. In Europe, onions have been cultivated since the 5th century, but large-scale cultivation did not begin until the Middle Ages [Ochar and Kim 2023]. Today, more than 5.5 million hectares are used to grow onions worldwide, and 99.5 million tonnes are produced annually [Eurostat 2023]. It is a vegetable with

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a two-year production cycle. The length of the growing season ranges from 80 to more than 120 days for spring-sown onions, which account for 90% of the total area under cultivation. Onion production is still one of the most developed sectors in the world despite high production costs, market volatility and income instability [Ochar and Kim 2023].

The antimicrobial and anti-inflammatory properties of onions are among the many known, and the chemical composition and its effects on the human body have been studied by many researchers [Bahram-Parvar and Lim 2018, Induja and Geetha 2018, Lante et al. 2020, Loredana et al. 2019, Marrelli et al. 2018, Petropoulos et al. 2017, Pöhnl et al. 2017]. Onions contain significant amounts of vitamins C and B and are also rich in fibre, calcium, essential oils and mineral salts. Onions and their peel contain various bioactive compounds such as organosulfur compounds (OSCs), thiosulfates, and polyphenols, including flavonoids and fructooligosaccharides (FOS) [Arshad et al. 2017, Fredotović et al. 2017, Khalid et al. 2022, Zhou et al. 2020]. The two main subgroups of flavonoids are anthocyanins, quercetin and quercetin derivatives, which are responsible for the different colours of onion skins, ranging from yellow to purple [Putnik et al. 2019, Sagar et al. 2018, 2021]. It also has a specific and unique flavour and a highly valued aroma. In terms of colour, there are three types of onion – red, yellow and white – all of which have different flavours and spiciness, ranging from mild to very strong [Khandagale and Gawande 2019]. Onions are consumed fresh, canned or processed into dried rings, flakes or powder. They are used in a variety of cuisines and recipes as condiments, salad toppings with other vegetables, and as ingredients in processed foods such as pastes and marinades [Edith et al. 2018, Piechowiak et al. 2020]. Soil, climatic and environmental conditions, cultivar, cultivation techniques, fertilizers and pesticides used, maturity stage and storage time and conditions have a significant impact on the bioactive compounds in onions [Ohanenye et al. 2019].

In recent years, Deep Neural Networks (DNNs) have become an important tool in the field of Artificial Intelligence (AI), a way of analysing data and making decisions based on it. DNNs, also known as deep machine learning or neural networks, are an excellent tool that can automatically detect patterns and classify objects based on colour [Abdulridha et al. 2020, Przybył et al. 2023, Rybacki et al. 2023], shape [Deng et al. 2017, 2021, Xie et al. 2023], texture [Grinblat et al. 2016, Rybacki et al. 2024], sound [Feng et al. 2022] or even generate new content [Shelke et al. 2022]. Machine learning and digital techniques provide new insights that can be applied to quality control of food and agricultural products [Franco et al. 2021, Li et al. 2021, Meenu et al. 2019].

A special type of DNN are Convolutional Neural Networks (CNNs), which show exceptional performance in the analysis of spatial data such as images. CNNs are designed to recognise patterns in three-dimensional spaces, making them effective tools in areas such as machine vision and computer vision analysis [Zheng et al. 2018]. CNNs consist of a convolutional layer, a pooling layer, an activation layer and a connection layer. The convolution layer is the core part of the CNN and uses a series of filters that are traversed over the image to detect local patterns such as edges, shapes or textures, the results of which are aggregated to form a feature map [Li et al. 2020]. The convolution layer is often followed by a pooling layer to reduce the size of the feature space. The most common type is the max-pooling layer, which selects the maximum value from a fixed-size window. The pooling layer is followed by an activation layer whose purpose is to make the architecture under development non-linear, usually using the ReLu (Rectified Linear Unit) function. The final layer is the connection layer, which is responsible for processing global features and making decisions based on earlier local detections. This layer is connected to the final output layer [Ma et al. 2024].

CNNs have a very wide range of applications in different fields and are used to solve complex problems at multiple levels, such as quality assessment of food and agricultural crops [Jean et al. 2015], object identification [Girshick et al. 2014, LeCun et al. 2015, Long et al. 2015, Raghu and Sriraam 2018, Russakovsky et al. 2015], human face recognition [Schroff et al. 2015] and traffic monitoring [Lemley et al. 2017a, 2017b]. CNN models have been used in medicine for the treatment of diseases such as breast cancer [Wang et al. 2016, Zheng et al. 2023], skin [Esteva et al. 2017] and brain cancers [Jermyn et al. 2015], autism and aneurysms in humans [Oord et al.

2016, Zhou and Troyanskaya 2015]. CNNs are also used in robotics for path planning of ground robots [Pfeiffer et al. 2017], path control of autonomous vehicles [Shalev-Shwartz et al. 2016], programming of production manipulators [Levine et al. 2016] and visual navigation [Gupta et al. 2017].

CNNs and image analysis are also widely used in the agricultural and agri-food industries to assess the quality of raw materials and food products. For example, these techniques are used to evaluate seeds and grains in terms of quality loss by quantifying the degree of mechanical damage, maturity, contamination with other plant species and infections [Patel et al. 2012, Rybacki et al. 2023]. The most important feature of these methods is the non-invasive assessment of the test material. In addition, the increasing computing power of computers gives machine analysis of images and CNNs a significant advantage over methods that destroy the material being evaluated [Mahajan et al. 2015, Patrício and Rieder 2018, Ramirez-Paredes and Hernandez-Belmonte 2020].

Machine learning and CNNs allow for the application of precision agriculture technologies and are used to analyse plant images to identify disease symptoms or the presence of pests, enabling rapid response and application of appropriate crop protection measures [Rybacki et al. 2021, 2022]. CNNs can analyse images of crop fields, identify stages of crop growth and predict potential yields. This allows farmers to better manage their crops and optimise production processes. They can also be used to analyse soil images to classify soil properties, which can help tailor fertilization strategies and other agricultural practices to specific soil conditions [Cao et al. 2024]. Analysis of satellite images using CNNs helps to monitor water resources in agricultural areas, leading to better irrigation management and avoidance of excessive water use. The use of CNNs to analyse meteorological data and satellite imagery facilitates the development of predictive yield models [Shahhosseini et al. 2021]. Farmers can adjust their strategies based on weather forecasts. Neural networks can also be integrated with agricultural robotic control systems, such as harvesting robots, to help guide farm machinery with precision and optimise field operations [Alkhadrawi and Alzboon 2024].

PURPOSE, MATERIAL AND STUDY METHODOLOGY

Definition of onion root classification criteria

For processing and the agri-food industry, for all quality classes, subject to the specific provisions for each class and the tolerances allowed, the onions must be clean, free from foreign matter and pests, sound and whole, without mechanical damage, excessive surface moisture and signs of frost damage (EC 1508/2001). In addition, the chives must be cleanly cut and less than 6 cm long (except for braided onions). The development and condition of the onions must permit their storage, transport, and handling.

Class I onions must be characteristic of the variety and be firm and compact, with no visible external growth on the stem and no roots. Defects may be allowed in this class, provided they do not affect the general appearance and quality of the onions, i.e. slight defects in shape, colour, small spots not covering 20% of the bulb surface, small superficial cracks in the outer skin, provided the fleshy skin is adequately protected.

Class II includes onions that do not satisfy the requirements of Class I but are sufficiently firm, with defects of shape and colour in the outer skin and traces of the outer skin, but not exceeding 10% by number or weight per package. Class II may show slight signs of abrasion, bruising and healed cracks, with roots, spots not extending to the last dry outer skin, cracks in the outer skins or partial absence of the outer skins on not more than 33% of the bulb, provided the fleshy skins are intact.

The size of the onion is determined by the maximum diameter of its cross-section. The difference in diameter between the smallest and the largest onion in a given package must not exceed: 5 mm if the diameter of the smallest onion is 5 mm or more but less than 15 mm. However, the difference may be 10 mm where the diameter of the bulb is 15 mm or more but less than 25 mm, 15 mm where the diameter of the smallest bulb is 25 mm or more but less than 40 mm, 20 mm where the diameter of the smallest bulb is 40 mm or more but less than 70 mm, 30 mm where the diameter of the smallest bulb is 70 mm or more.

Tolerances with respect to quality and size are allowed in each lot for produce that does not satisfy the requirements of the class indicated. For Class I, a quality tolerance of 10% by number or weight is allowed for onions that do not satisfy the requirements of the class but meet the requirements of Class II or, exceptionally, falling within the tolerances of that class. In Class II, a quality tolerance of 10% by number or weight is allowed for onions that do not satisfy the requirements of the class or the minimum requirements, except for produce affected by rotting or any other deterioration rendering it unfit for consumption or processing. For all classes, a quality tolerance of 10% by number or weight is allowed for onions that do not satisfy the size requirements, but should have a diameter not more than 20% above or below that size.

For the classification of onions in this study, the quality thresholds directly assigned to the quality classes were determined on the basis of the maximum diameter of the cross-section and the area of damage or discolouration of the skin. As shown in Table 1, five quality thresholds were assumed for each class.

Preparation of the dataset

The main objective of this study was to build an automatic classification model for onions in terms of geometric parameters and their damage. The onion used for the study was the hybrid variety Hyduro F1 of the Rijnsburger type, which is characterised by a high dry matter content of 12–13% and strong, bright and well-coloured skin. The onions were obtained from a farm situated in the village of Dąbrowa Biskupia (52°78'N, 18°55'E), Kujawsko-Pomorskie province. The variety is well adapted to European soil and climate conditions, as its strong root system allows it to be grown on lighter soils and produce a high percentage of large onions when thinly sown. The variety is ideal for both direct processing and long-term storage.

The photos of 1,082 onions were taken using a digital camera Olympus SP-810UZ 14 MEGAPIXEL with a 1/2.3 inch class sensor and a resolution of

Table 1. Quality standards and grading criteria for onions

Class	Quality standard	Onion diameter range (mm)	Onion perimeter range (mm)	Range of cross-sectional area of the onion (mm)	Acceptable surface discolouration and damage to onion skins (%)
1st	W1_P	5.00 – 15.00	15.70 – 47.10	193.49 – 1741.45	<174.15
	W2_P	15.01 – 25.00	47.13 – 78.50	1743.78 – 4837.37	174.38 – 483.74
	W3_P	25.01 – 40.00	78.53 – 125.60	4841.24 – 12383.66	484.12 – 1238.37
	W4_P	40.01 – 70.00	125.63 – 219.80	12389.85 – 37924.95	1238.99 – 3792.50
	W5_P	>70.01	>219.83	>37935.79	>3793.58
2nd	W1_D	<15.00	<47.10	<1741.45	<348.29
	W2_D	15.01 – 25.00	47.13 – 78.50	1743.78 – 4837.37	348.75 – 967.47
	W3_D	25.01 – 40.00	78.53 – 125.60	4841.24 – 12383.66	968.25 – 2476.73
	W4_D	40.01 – 70.00	125.63 – 219.80	12389.85 – 37924.95	2477.97 – 7584.99
	W5_D	>70.01	>219.83	>37935.79	>7587.16
3rd	W1_T	–	–	–	<348.29
	W2_T	–	–	–	<967.47
	W3_T	–	–	–	<2476.73
	W4_T	–	–	–	<7584.99
	W5_T	–	–	–	<7587.16

Fig. 1. Imaged onion of the Hyduro F1 variety

4288 × 3216 (14 million) pixels. The camera was equipped with a 36x optical zoom lens, and with the shortest focal length of 24 mm, the resulting maximum aperture was 1:2.9. Onion images were taken at maximum zoom, and the imaging surface was at a distance of 40 cm from the lens. The chamber was illuminated by three light sources at 800 lumens, with a blue and non-reflective surface. The photo files were initially stored in the camera's internal memory and then saved to the computer's memory at 96 dpi resolution and 2139 × 1888 size (Fig. 1).

In addition, each onion imaged was measured for weight, maximum diameter, height, longitudinal and transverse circumference, longitudinal and transverse cross-sectional area, and the condition of the skin and the presence of damage or discolouration on the skin was assessed visually. The result of this assessment was the percentage of discolouration or damage. Each onion imaged was marked with a code from H0001 to H1082, which corresponded to the code of the photograph. The values of the geometric parameters are given in Table 2.

Image pre-processing

In order to process and analyse the onion images, they need to be digitised spatially and amplitude-wise. This involves converting the image information from a continuous form to a discrete form so that the image can be represented by numbers (pixels) and stored as a digital file [Fauziah et al. 2024]. The digitisation of spatial coordinates (x, y) is called image sampling, and the digitisation of amplitude is called greyscale quantisation. The result of sampling the onion images selected for analysis is to obtain a sample of colour values (image pixels) at regular intervals. The result of quantisation, on the other hand, is to determine the range of values that each sample can take. For example, in the case of greyscale images, each sample can have a value from 0 to 255. To evaluate the results of the quantisation of the colour of damage and discolouration of onion skin, the mean square error in RGB space, denoted as Mean Square Error (MSE) or Root Mean Square Error (RMSE) and the Peak Signal to Noise Ratio (PSNR) expressed as a logarithmic measure in dB according to equations 1–3 [Mohammed et al. 2023]. Example parameter values for the onion image discretisation method are given in Table 3.

$$RMSE = \sqrt{\frac{1}{3mn}\sum_{j=1}^{M}\sum_{i=1}^{N}\left[\left(R_{ij}-R_{ij}^{*}\right)^{2} + \left(G_{ij}-G_{ij}^{*}\right)^{2} + \left(B_{ij}-B_{ij}^{*}\right)^{2}\right]} \quad (1)$$

$$MSE = \frac{1}{3mn}\sum_{j=1}^{M}\sum_{i=1}^{N}\left[\left(R_{ij}-R_{ij}^{*}\right)^{2} + \left(G_{ij}-G_{ij}^{*}\right)^{2} + \left(B_{ij}-B_{ij}^{*}\right)^{2}\right] \quad (2)$$

$$PSNR = 20\log_{10}\frac{255}{RMSE} \quad (3)$$

where:
R_{ij}, G_{ij}, B_{ij} – the colour components of the original image,
R^{*}_{ij}, G^{*}_{ij}, B^{*}_{ij} – the colour components of the image resulting from quantisation,
M, N – spatial resolution of the image.

Software

The photo analysis algorithms were built using the Python 3.9 programming language in the scientific computing environments (libraries) TensorFlow 2.0, Keras, Scipy, Numpy, OpenCV. TensorFlow 2.0 is an open-source machine learning library developed by Google. It is one of the most popular frameworks

Table 2. Codes, real geometric quantities and mass of the imaged onion

Onion's code	Mass (g)	Maximum diameter (mm)	Height (mm)	Perimeter		Sectional area		Discolouration and damage (%)
				transverse (mm)	longitudinal (mm)	transverse (mm^2)	longitudinal (mm^2)	
H0001	144.01	69.28	65.56	217.65	209.96	3769.69	3375.73	9.33
H0002	152.19	71.78	57.74	225.50	184.40	4046.66	2618.44	5.03
H0003	132.77	63.24	54.95	198.58	175.54	3139.49	2370.31	4.43
H0004	124.07	59.10	51.35	185.56	164.24	2741.53	2069.85	1.04
H0005	163.67	77.96	67.74	244.79	215.70	4770.87	3601.99	4.32
H0006	111.32	53.02	46.07	166.49	147.67	2207.02	1666.29	3.62
H0007	131.34	62.56	54.36	196.44	173.68	3072.23	2319.52	10.22
H0008	123.11	58.64	50.95	184.13	159.99	2699.27	2037.94	2.88
H0009	167.59	79.83	69.36	250.65	219.79	5002.14	3776.60	9.45
H0010	147.75	70.38	61.15	220.98	195.01	3887.90	2935.35	0.98
…	…	…	…	…	…	…	…	…
H1073	109.55	52.18	45.34	163.85	144.37	2137.39	1613.73	0.88
H1074	100.66	47.95	41.66	150.55	132.81	1804.57	1362.44	2.85
H1075	161.09	76.73	66.67	240.93	209.35	4621.65	3489.33	9.33
H1076	157.34	74.94	65.12	235.32	207.47	4408.98	3328.76	5.03
H1077	175.21	83.46	72.51	262.05	229.70	5467.36	4127.84	4.43
H1078	121.43	57.84	50.26	181.61	159.81	2626.10	1982.70	1.04
H1079	143.78	68.48	59.51	215.04	188.85	3681.77	2779.72	4.32
H1080	134.67	64.15	55.74	201.42	175.01	3229.99	2438.63	3.62
H1081	122.49	58.34	50.70	183.20	159.18	2672.15	2017.47	10.22
H1082	156.04	74.32	64.58	233.38	204.78	4336.42	3273.99	2.88

Table 3. Average values for the discretisation process parameters of onion images

Average	H0001	H0002	H0003	…	H0575	H0576	H0577	…	H1080	H1081	H1082
PSNR (dB)	150.55	151.52	149.65	…	148.78	154.54	159.22	…	151.11	147.99	152.25
MSE	89.34	89.55	88.84	…	89.88	87.99	90.04	…	91.01	90.44	90.24

for the efficient implementation of neural networks [Singh and Manure 2020].

Keras is a specialised, high-level application programming interface (API) for building and training deep machine learning models. Originally developed as a standalone library, it is now an integral part of TensorFlow 2.0, making it one of the most popular interfaces for building models in the TensorFlow environment.

SciPy is an open-source library for scientific programming in Python. It is a comprehensive set of tools and functions that facilitate a wide variety of tasks related to data analysis, numerical computation, optimisation, signal processing, linear algebra, statistics and many other areas related to science and engineering.

NumPy contains array data and basic data operations such as sorting, indexing, etc., while SciPy consists of all numeric code.

OpenCV (Open Source Computer Vision Library) is an open-source library for computer image analysis and processing. It is widely used to develop applications in computer vision, robotics, object recognition, motion tracking, and many other fields, including agriculture and the agri-food industry [Qi et al. 2024].

Loading and preliminary processing of the dataset

The first step in the process of classifying and assessing the quality of the bulbs is to load their images into NumPy arrays of the 'uint8' data type. This range is sufficient to store pixel information in RGB images. The data was prepared using two TensorFlow 2.0 modules. The first is tf.io, which is used to load and store input data, and the second is tf.image, which is used to resize images and decode the raw content.

At the beginning of the analysis, the contents of the files were checked against the pathlib library and lists of onion image names were generated. These were then visualised and resized according to code 1 in Figure 2 (https://github.com/piotrrybacki/onion-CNN.git).

The displayed file list shows that the dataset contains 1082 images of the Hyduro F1 onion variety, taking up approximately 4.5 GB. These images were labelled with the symbol of the onion being imaged. They were then ordered chronologically and randomly divided into three subsets: a learning set of 282 trials (images) and validation and test sets of 400 trials (images) each. The automatic and random copying of images from the source catalogue to the learning, validation and test folders was enabled by code 2 (https://github.com/piotrrybacki/onion-CNN.git).

Fig. 2. Visualisation of onion photos

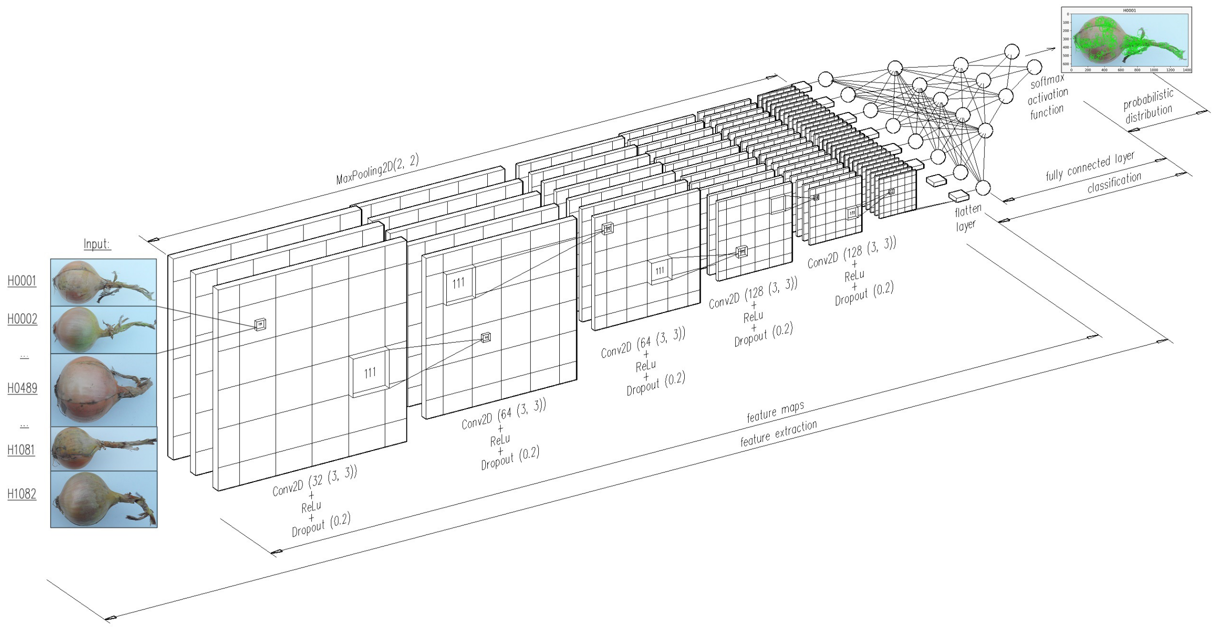

Fig. 3. Diagram of an implemented CNN in onion quality classification (OnionNET)

Architecture of the multi-layer CNN

The Keras interface was used to implement the network. Due to the extensive analysis and geometric classification of onion images, the overall structure of the CNN is an alternating arrangement of six classes: Conv2D (with activation function ReLu), MaxPooling2D and Dropout. As shown in Figure 3, each splice layer was followed by a merging layer for subsampling, which reduced the size of the feature map. The MaxPooling2D class creates max-type connection layers. The size of the pooling range (pool size = 2), e.g. 2×2, means that a maximum value is selected from the range of the 2×2 matrix by one stride (strides = 1) at a time.

In the analysis performed, the input tensor was transformed into object maps of size 200×200, and finally, just before the flattening layer, an object map of size 7×7 was obtained. Within the developed network architecture, the depth of the object maps gradually increases from 32 to 128. Listing 3 (https://github.com/piotrrybacki/onion-CNN.git) shows the programming code for the model in Figure 3.

The next step of the model under construction is to plot the loss curves and the values of the accuracy of the analysis, the values of the geometric parameters, the accuracy of the quantification of the onion quality and its prediction according to Code 4 (https://github.com/piotrrybacki/onion-CNN.git).

The final stage of the analysis is to display the result of the predictions in the form of probabilities of belonging to the various quality classes of onions based on the adopted benchmarks, taking into account weight, diameter and any damage or discolouration of the husk. The tf.argmax function searches for onion photos with the highest probability of belonging to the patterns and assigns the corresponding label, which is the onion's image code, and assumed geometric parameters, i.e. diameter, height, circumference and estimated damage or discolouration of its scales. This was done for the whole set of 1082 images, and both the input data and the predicted labels were visualised according to Code 5 (https://github.com/piotrrybacki/onion-CNN.git).

The developed onion classification model was also evaluated for performance using measures of speed of operation and prediction accuracy. The speed of the model was measured by the classification rate, expressing the number of assigned images per second and the average classification time of a single onion picture. The accuracy of the model was assessed using the Predictive Precision Value (PPV) and Total Prediction Performance (TPR) indices, as well as the score correction factor (f) and its accuracy (ACC). These metrics were determined using equations 4–7.

$$PPV_X = \frac{TP_X}{TotalPredicted_X} \tag{4}$$

$$TPR_X = \frac{TP_X}{TotalPredicted_X} \tag{5}$$

$$fscore_X = \frac{1}{\frac{\propto}{PPV_X} + \frac{\propto}{TPR_X}} \tag{6}$$

where:
α = 0.5 assigns equal weight to TPR and PPV

$$ACC = \frac{\sum_{i=1}^{n} \frac{TP_i}{I_i}}{n} \tag{7}$$

where:
n = No. of classes,
Ii = No. of images in class *i*.

Quality measure X in onion classification, if *TPx* is the true positive score, i.e. the number of onion images correctly recognised and assigned to class *X*. *PPVx* is the number of true positives divided by the total number of onion images predicted to belong to class *X*. *TPRx* is defined as the number of true positives divided by the actual number of onion images in class *X*. The *f-scoreX* factor is used to combine *PPVx* and *TPRx* into a single measure using a harmonic mean. The overall accuracy in equation 8 was calculated using a balanced accuracy that normalises the true positive score for each class by the number of bulb images in the class and divides the sum by the number of quality benchmarks applied. Balanced accuracy ensures that all classes contribute equally to the calculation of the overall model accuracy, even if the number of onion images in the classes is unequal. To illustrate the accuracy of the onion classification, the paper uses confusion matrix models in the format shown in Figure 4.

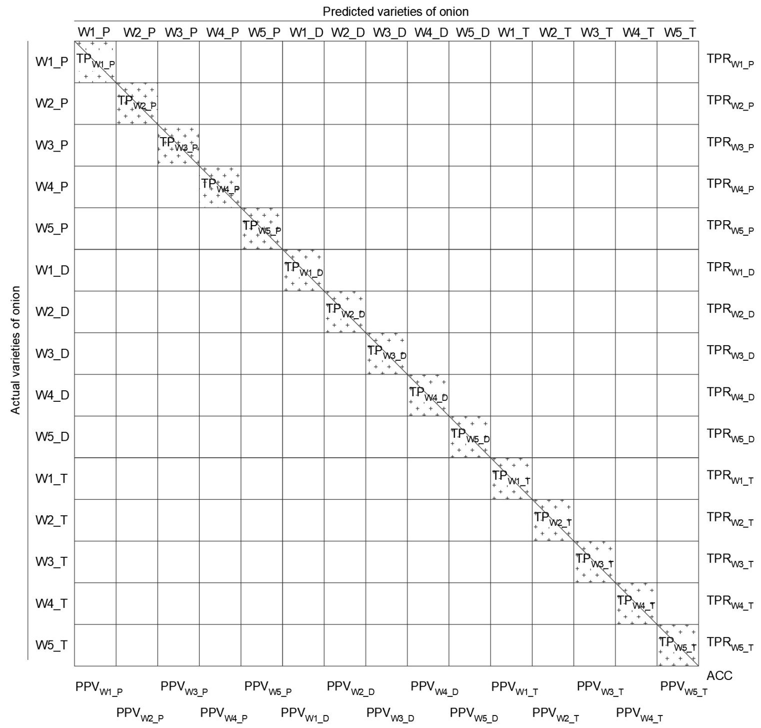

Fig. 4. Confusion matrix scheme for geometric classification of onions

ANALYSIS OF RESULTS

The research and analysis carried out allowed the development of a CNN architecture and codes in Python 3.9 that allow automatic comparison, classification, and comparison with an accepted benchmark based on onion diameter and assessment of the degree of damage or discolouration of the onion skin. Table 4 illustrates the variation in map size as a function of the number of layers of the CNN model developed. As the data shows, each hidden layer of the CNN model results in progressively smaller maps, resulting in 9,788,484 parameters in the output.

The CNN architecture and the code developed for it allowed the automatic and random sorting of the onion images into training, validation and test directories, followed by unsupervised model training and validation, the results of which are shown in Figure 5.

The accuracy of the learning process of the proposed CNN model in classifying onions according to the assumed patterns was 92.23%, and the accuracy of its validation was 86.74% (Figure 5a). The loss curve, on the other hand, shows (Figure 5b) that in the process of training the model in assigning an image to a pattern, the accuracy was 19.23%, and in the process of its validation, it was 36.46%.

The developed algorithms and code 5 (https://github.com/piotrrybacki/onion-CNN.git) allow the contour detection of the imaged onion with simultaneous determination of its diameter, height, longitudinal and transverse circumference and cross-sectional area (Fig. 6).

In terms of qualitative classification, it is also extremely important to be able to detect and estimate the area of damage or discolouration of the skin. As shown in Figure 7 for randomly selected images, the proposed algorithms and code 6 (https://github.com/piotrrybacki/onion-CNN.git) mark the detected damage with circles and indicate their areas.

In addition, the automatically plotted histograms, of which three examples are shown in Figure 8, allow the calculation of the value and the number of pixels per unit area of the analysed onion. The significant peak in the graph shows that the proportion of discolouration and skin damage is highest in this area.

Table 4. Variation in map size according to layer number of the developed CNN model.

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None, 198, 198, 32)	896
max_pooling2d (MaxPooling2D)	(None, 179, 179, 32)	0
dropout (Dropout)	(None, 179, 179, 32)	0
conv2d_1 (Conv2D)	(None, 117, 117, 32)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 98, 98, 32)	0
dropout_1 (Dropout)	(None, 98, 98, 32)	0
conv2d_2 (Conv2D)	(None, 66, 66, 64)	173856
max_pooling2d_2 (MaxPooling2D)	(None, 43, 43, 64)	0
dropout_2 (Dropout)	(None, 43, 43, 64)	0
conv2d_3 (Conv2D)	(None, 41, 41, 64)	647584
max_pooling2d_3 (MaxPooling2D)	(None, 30, 30, 64)	0
dropout_3 (Dropout)	(None, 30, 30, 64)	0
conv2d_4 (Conv2D)	(None, 24, 24, 128)	1516262
max_pooling2d_4 (MaxPooling2D)	(None, 17, 17, 128)	0
dropout_4 (Dropout)	(None, 17, 17, 128)	0
conv2d_5 (Conv2D)	(None, 21, 21, 128)	6586862
max_pooling2d_5 (MaxPooling2D)	(None, 10, 10, 128)	0
dropout_5 (Dropout)	(None, 10, 10, 128)	0
conv2d_6 (Conv2D)	(None, 19, 19, 128)	8984851
max_pooling2d_6 (MaxPooling2D)	(None, 7, 7, 128)	0
dropout_6 (Dropout)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 12800)	0
dense (Dense)	(None, 512)	9556162
dense_1 (Dense)	(None, 1)	513

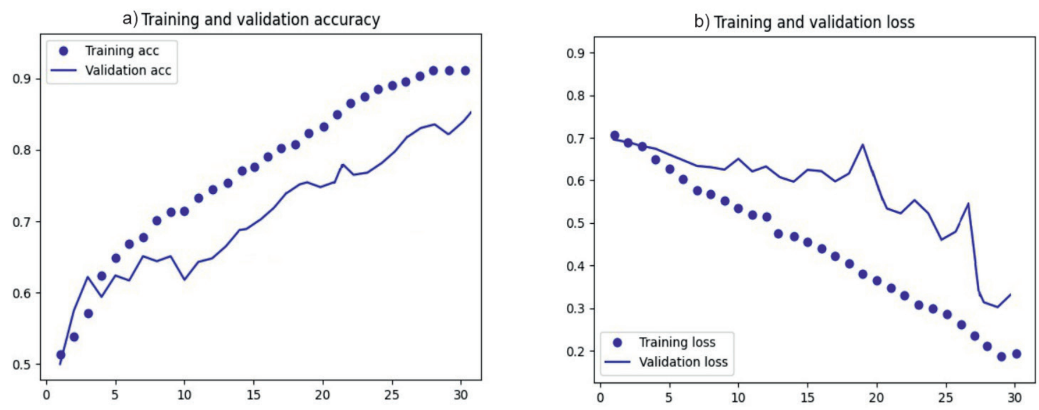

Fig. 5. Visualisation of loss function curves and learning accuracy and validation for the created CNN when classifying onion images according to assumed patterns: a) training and validation accuracy, b) training and validation loss.

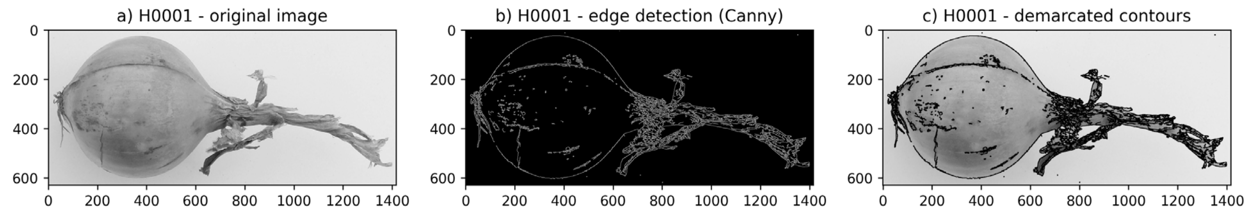

Fig. 6. Contour detection of the imaged onion using image H0001 as an example: a) original image, b) edge detection (Canny), c) delineated onion contours

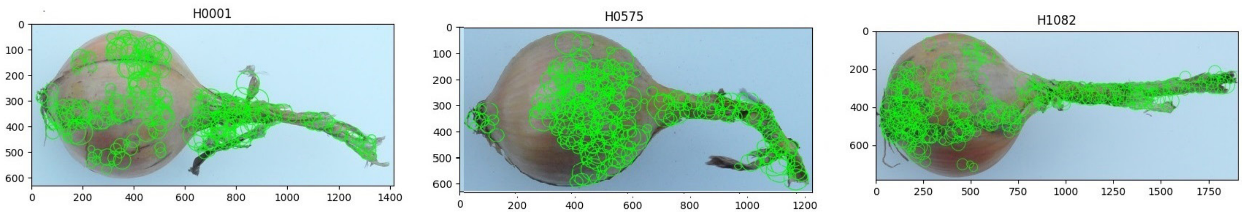

Fig. 7. Detection of areas of damage or discolouration of onion skins

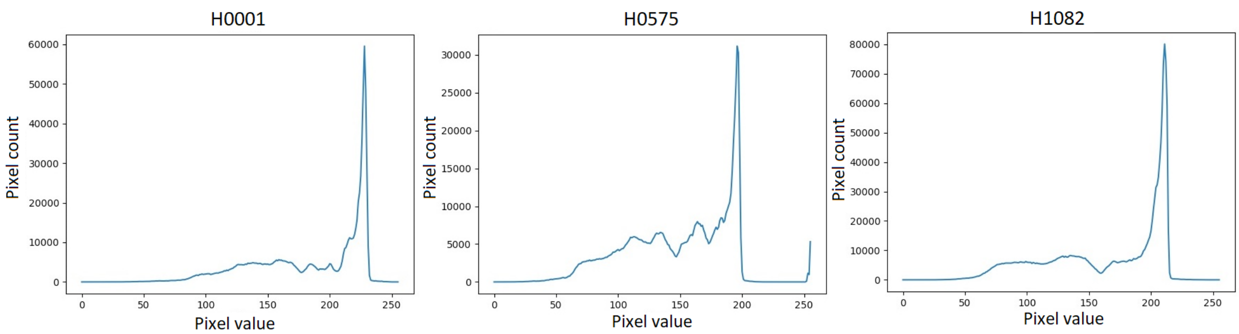

Fig. 8. Histogram of the numbers and pixel values of the onion images analysed

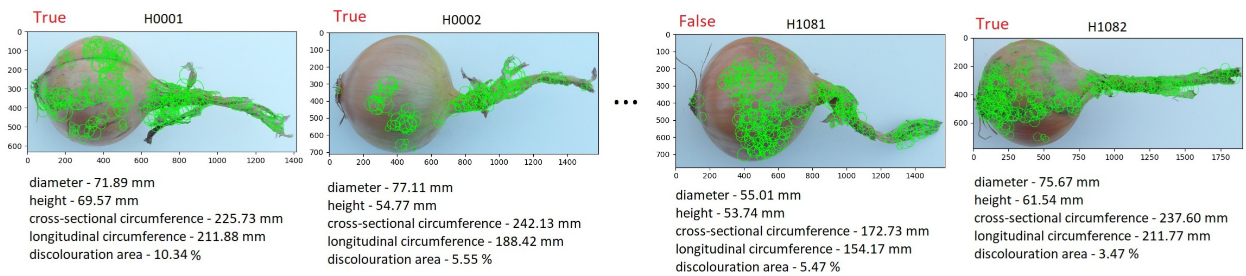

Fig. 9. Histogram of the numbers and pixel values of the onion images analysed

Table 5. Data from labels generated by the algorithms and CNN model

Code	Maximum diameter reading (mm)	Accuracy of diameter reading (%)	Height readout (mm)	Accuracy of height reading (%)	Reading of the circumference transverse (mm)	Accuracy of circumference reading transverse (%)	Circumference reading longitudinal (mm)	Accuracy of circumference reading longitudinal (%)	Discolouration and damage (%)	Accuracy of reading discolouration and damage (%)
H0001	71.89	3.63	69.57	5.76	225.73	3.58	211.88	2.79	10.34	9.77
	77.11	6.91	54.77	5.42	242.13	6.87	188.42	3.73	5.55	9.37
H0003	66.89	5.46	57.85	5.01	210.03	5.46	168.44	2.44	4.67	5.14
H0004	54.55	8.33	48.44	6.01	171.29	8.33	167.25	3.60	1.14	8.77
H0005	74.15	5.14	64.79	4.55	232.83	5.14	219.73	3.20	4.62	6.49
H0006	53.99	1.79	43.03	7.07	169.53	1.79	149.68	3.35	3.82	5.24
H0007	63.50	1.48	58.86	7.65	199.39	1.48	176.69	3.40	9.28	10.13
H0008	56.02	4.68	47.55	7.15	175.90	4.68	154.96	3.25	2.99	3.68
H0009	85.81	6.97	68.38	1.43	269.44	6.97	211.89	2.79	10.45	9.57
H0010	67.57	4.15	63.35	3.47	212.17	4.15	199.11	3.57	0.87	12.64
…	…	…	…	…	…	…	…	…	…	…
H1073	55.87	6.60	47.36	4.27	175.43	6.60	147.47	3.46	0.78	12.82
H1074	45.65	5.03	42.63	2.27	143.34	5.03	135.82	3.69	2.95	3.39
H1075	79.09	2.98	69.65	4.28	248.34	2.98	213.36	1.88	11.31	9.02
H1076	70.09	6.92	63.13	3.15	220.08	6.92	201.48	1.49	8.78	11.50
H1077	88.65	5.86	77.55	6.49	278.36	5.86	219.71	3.63	6.66	16.52
H1078	54.37	6.38	52.24	3.80	170.72	6.38	151.71	4.02	14.90	6.71
H1079	65.99	3.78	56.56	5.21	207.21	3.78	192.86	3.12	8.99	12.24
H1080	69.14	7.22	52.73	5.70	217.10	7.22	181.11	3.37	15.11	13.24
H1081	55.01	6.06	53.74	5.67	172.73	6.06	154.17	3.25	5.47	10.97
H1082	75.67	1.78	61.54	4.94	237.60	1.78	211.77	4.24	3.47	11.53
Average	5.06		4.97		5.05		3.21		9.44	

Table 6. Summary of misattributed labels in the onion image grading process

Quality standard	Number of images of onions in the quality standard	Number of errors	Percentage share (%)	Error in onion image attribution														
				W01_P	W02_P	W03_P	W04_P	W05_P	W01_D	W02_D	W03_D	W04_D	W05_D	W01_T	W02_T	W03_T	W04_T	W05_T
W01_P	65	6	9.23		1	0	2	1	0	0	1	0	1	0	0	0	0	0
W02_P	57	9	15.79	0		1	0	4	2	1	1	0	0	0	0	0	0	0
W03_P	111	7	6.31	1	0		1	2	0	1	0	1	0	0	0	1	0	0
W04_P	167	9	5.39	1	0	0		4	0	1	0	2	1	0	0	0	0	0
W05_P	191	16	8.38	0	1	1	3		3	2	5	0	0	0	1	0	0	0
W01_D	32	10	31.25	2	1	1	1	1		1	1	2	0	0	0	0	0	0
W02_D	67	9	13.43	0	1	1	0	0	1		2	2	0	1	0	0	1	0
W03_D	112	12	10.71	1	2	1	1	2	2	0		2	1	0	0	0	0	0
W04_D	134	10	7.46	1	2	1	1	2	1	1	0		1	0	0	0	0	0
W05_D	111	4	3.60	0	1	1	0	0	1	0	1	0		0	0	0	0	0
W01_T	11	1	9.09	0	0	0	0	0	0	0	0	1	0		0	0	0	0
W02_T	14	1	7.14	0	0	0	0	0	0	1	0	0	0	0		0	0	0
W03_T	5	1	20.00	0	0	0	0	0	0	0	1	0	0	0	0		0	0
W04_T	3	1	33.33	0	0	0	0	0	0	1	0	0	0	0	0	0		0
W05_T	2	0	0.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Total	1082	96	91.13	6	9	7	9	16	10	9	12	10	4	1	1	1	1	0

The algorithm proposed in the paper searched for the image with the highest probability to the pattern, assigning it a corresponding label, which is a set of information calculated from the image shape and number of pixels about the geometric parameters of the onion. The label includes information on the diameter, height, transverse and longitudinal circumference, and the area of damage or discolouration of the skin expressed as a percentage of the total cross-sectional area. The label also contains information on the matched pattern and, thus, the assigned quality class of the onion. Figure 9 shows four example images of onions out of 1,082 analysed, with label and quality class assigned. A 'True' label was added to the onion image with the correct quality classification, and a 'False' label was added to the onion image with the incorrect label assignment.

Table 5 summarises the data generated by the developed model. This compilation was compared with empirical measurements of diameters, heights, transversal and longitudinal circumferences and estimated areas of discolouration or damage to the onion skin. It was found that the diameter of the imaged onion was read from the number of pixels with an average error of 5.06%, and the height was read with an average error of 4.97%. In contrast, the mean difference in accuracy for the detection of discolouration or damage to the onion skin was 9.44%.

Furthermore, the classification of onion images alone was achieved with an accuracy of 91.85%, i.e. 88 onion images were misclassified. Onion images of class I according to standards W1_P to W5_P were misclassified 43 times, of class II, according to quality standards W1_D to W5_D, 42 times and out of class III times (Table 6). This indicates that the problem is not in reading the geometric quantities from the photo alone but in estimating the area of damage. However, by using the number of onions in the quality patterns of the commodity class of the generated waste as the basis for classification, the model's accuracy increases to 91.13%.

The performance of the proposed CNN model was determined using the confusion matrix and the validation data set, and the analysis was divided into three stages. The first stage was the classification based only on the geometric parameters of the onions, with an accuracy of 89.07% (Figure 10c). Initially, only colour was considered, and onions were classified based on skin damage and discolouration, achieving an accuracy of 90.21% (Figure 10b). The model with the highest accuracy (91.85%, Figure 10a) classified onion images based on geometric parameters and skin colour.

Three analysis variants were performed to check the average classification time and the identification of onion images. These included classification based on the geometric parameters of the onion, damage or discolouration of the skin, and a third combining the previous two. A GPU (Graphics Processing Unit) was used for each analysis. As shown in Table 7, the fastest classification of onion images was based on geometric parameters alone (21.11 ms/image), while it took slightly longer (24.43 ms/image) to estimate damage size and skin discolouration based on colour. The longest time, 28.98 ms/image, was required to classify images using a combination of criteria, i.e. using geometric

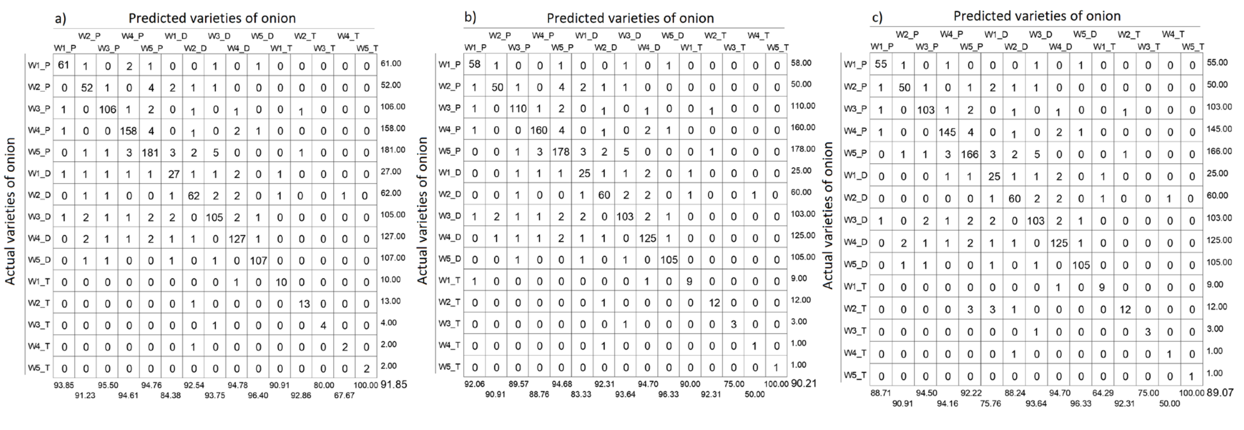

Fig. 10. Histogram of the numbers and pixel values of the onion images analysed

Table 7. Performance of the proposed onion quality classification model

Classification type	ACC (%)	PPV (%)	TPR (%)	fscore (%)	Average classification time GPU (ms/image)
Geometric parameters	89.07	86.39	85.29	87.99	21.11
Colour	91.91	87.98	87.87	92.22	24.43
Colour and geometric parameters	91.85	92.45	93.66	94.23	28.98

*GPU: NVIDIA GeForce RTX Studio 2060, 32 GB

parameters and colour. The combination of classification criteria increased the accuracy of the process, reaching up to 91.85% for the proposed model.

DISCUSSION

The quality classification of onions and the assessment of the healthiness of their skins is an extremely important part of their processing, storage and further processing in the salt and food industries and plays a key role in the production of high-quality products [Ochar and Kim 2023]. However, the qualitative quantification of onions is characterised by high labour intensity, low productivity and accuracy, relying mainly on manual work. Methods are therefore being sought to automate this process, thereby increasing accuracy and efficiency. Image analysis and artificial neural networks offer new possibilities and are becoming useful tools in multi-criteria decision-making [Przybył et al. 2023].

The onion classification method presented in this study, based on qualitative patterns, achieved an accuracy of 91.85% and did not differ from other such models presented in scientific papers for the quantification and diagnosis of onion diseases and other agricultural crops used as raw materials in the agri-food industry [Nath et al. 2024]. The root mean square error (MSE) in RGB space varied between 87.99 and 91.24, and the maximum image classification time was 28.98 ms/image. Kim et al. [2020] developed a model based on onion skin colour and discolouration to identify onion diseases. The authors evaluated the efficiency of this model in identifying disease symptoms visible on the onion surface using the medium average precision (mAP) metric and obtained values ranging from 74.10 to 87.20. Arfah et al. [2023] proposed a model based on Bayes and CNN algorithms with GLCM feature extraction for the identification and classification of onion diseases. According to the authors, their proposed model classifies disease symptoms and determines the level of disease with an accuracy close to 100.00%. Puspadhani et al. [2021] applied CNNs and deep-learning techniques to the classification of onions and garlic. The proposed network architecture classified images with an accuracy of more than 80.00% and featured a kernel size of 3×3, a learning rate of 0.01, an activation function of ReLu and an epoch number of 70.

Classification based on geometric parameters is also used in the qualitative evaluation of other vegetables. Similar to this study, but for the quality classification of carrots, Deng et al. [2021] proposed to automatically assess their quality based on colour. Based on ShuffleNet, the authors constructed a deep learning model (CDDNet) to detect surface defects in carrots. Experimental results showed that the detection accuracy of the proposed model was 93.01% for multi-class classification. The accuracy of pattern-matching classification reached 92.80%, similar to that of the current study. Carrot classification based on geometric shapes was also applied by Xie et al. [2019], where six parameters of shape and six parameters of colour were extracted, resulting in 12 input parameters. The authors proposed models based on Back Propagation in Neural Networks (BPNN), Support Vector Machines (SVM) and Extreme

Learning Machines (ELM), whose average accuracy of geometric parameter extraction and classification was 96.67%. In another study, Xie et al. [2019b] obtained a model accuracy of 90.9% based on five quantitative indicators that define the quality of carrot roots. On the other hand, Deng et al. [2017] developed a method to detect geometric defects in carrot roots, and experimental results using this method showed a detection accuracy of 88.30 to 98.00%.

CONCLUSIONS

This study proposes a CNN architecture and a model for the automatic classification of onion images based on their geometric parameters and the colour used to detect damage or discolouration of the skin. The algorithm, described by the code, allows the definition of any number of classes (quality patterns) and the analysis of any number of images copied to training, validation and test catalogues, significantly increasing its utility.

The onion classification method presented in this study, based on qualitative patterns, achieved an accuracy of 91.85% and did not differ from other such models presented in scientific papers for the quantification and diagnosis of onion diseases and other agricultural crops used as raw materials in the agri-food industry. The root mean square error (MSE) in RGB space varied between 87.99 and 91.24, and the maximum image classification time was 28.98 ms/image.

Overall, it can be concluded that the classification of onions on the basis of geometrical parameters and the detection of damage or discolouration of their skin allows a precise qualitative classification and the assignment of an appropriate pattern. The detection of skin discolouration also allows the elimination of damaged or diseased onions.

DATA AVAILABILITY STATEMENT

All relevant data for this study are publicly available from the Github repository: https://github.com/piotrrybacki/onion-CNN.git.

CONFLICT OF INTEREST

There is no conflict of interest to declare.

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